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DETERMINANTS OF GOLD PRICE MOVEMENTS: AN EMPIRICAL INVESTIGATION IN THE PRESENCE OF MULTIPLE STRUCTURAL BREAKS

Themba Gilbert Chirwa¹ and Nicholas M. Odhiambo

Abstract

This study investigates the short- and long-run determinants of gold price movements in financial markets by taking into account multiple structural breakpoints using an ARDL-based error correction approach. The study used daily time series data from December 19, 2018 to May 15, 2020. The key variables used include international stocks and bond funds that are frequently traded on stock exchanges around the world. The results, based on the fourth breakpoint regime, reveal a significant positive relationship between gold price movements and LSE, Nikkei stocks, T.Rowe global multi-sector bond funds, and CBOE volatility index; and a significant negative association with Gmo emerging country debt and Pimco emerging markets local currency bond funds both in the short- and long-run. Other stocks, like NASDAQ, DJI, S&P500, only revealed negative short-run relationships; except for NYSE that was found to have a positive short-run association with gold price movements. Conversely, Goldman Sachs bonds revealed a significant positive long-run relationship with gold price movements. These results have significant policy implications for gold producers and investors, as both stocks and bonds are an important source of information in the determination of gold price movements both in the short- and long-run.

Keywords: Gold prices; Cryptocurrencies; Stocks; Bonds; ARDL; Cointegration

JEL Classification Code : E31, L16, D53, E44, G15, Q02

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1. Introduction

Gold has for centuries been a representation of wealth and is regarded as a safe haven when economies grow or recess over time (Baur & Lucey, 2010; Chan *et al.*, 2011; Ciner *et al.*, 2013). In ancient times, gold was used as a medium of exchange by minting coins in communities around the world (Rothbard, 1995). During the gold standard era that ended in the 1930s, gold was used as a currency reserve to back up any amount of issued currency from central banks around the world. Much as the latter half of the 20th century abandoned the gold standard; this precious metal continues to be traded on the stock market as a safe haven in situations of economic, financial or political prosperity or distress. Given that it is a popularly traded financial security, gold has all the qualities of being a strategic investment asset (Bariviera *et al.*, 2019). In March 2020, the London Bullion Market Association reported a two-decade high of \$46.4 billion value of gold traded on the stock exchange (Sykora, 2020). As a result, the investigation into the price dynamics of the commodity price of gold is of great importance to both producers and investors.

Hutcheson (1694-1746), who used to be Adam Smith's teacher, argued that commodities are likely to be used as money on the market, particularly those that are generally desirable and acceptable as a medium of exchange; are durable for longer periods; have a high value per unit weight; and are divisible into small units without losing their share of value. Based on these qualities, he argued that this was the basis as to why gold and silver have for centuries been the two best commodities chosen by society as the most suitable money backed by coins that carry their value as a warranty of purity (Rothbard, 1995).

In 1971, the world completely abandoned the gold standard to support fiat currency as a legal tender whose value is now backed by governments. However, the debasement of coins over time,

much as its main objective has been to increase the supply of money in the economy, has ended up raising the prices of goods and services. Compared to the gold standard, which managed to put in check government spending and inflation, the switch to fiat currency has, on the other hand, failed to contain inflationary pressures on the value of money, thereby necessitating the continued use of gold and silver as safe havens (Baur & Lucey, 2010; Chan *et al.*, 2011). The emergence of cryptocurrencies is also an interesting phenomenon whose main general principle is to cushion the continued debasement of fiat currencies due to inflationary policies enacted by governments around the world (Selmi *et al.*, 2018). Commonly referred to as the internet of value, the blockchain technology has created virtual gold and has taken the financial market to a new level where the attempt is to create a virtual currency whose supply and demand is based on the interactions between market participants and not necessarily by the actions of governments and central banks (Bouri *et al.*, 2017). Much as the development of blockchain technology is advancing, it is still at its infant stage of development.

The interchange between fiat currency and gold prices has necessitated this study to investigate the key factors that drive or hinder the growth of gold prices as a safe haven, both in the short- and long-run. Much as there are numerous studies on this precious commodity, little has been done to investigate the key determinants of it. There are four main reasons why this study makes an important contribution to the literature.

Firstly, most studies have focused on annual data which limits the investigation into the real determinants of gold price movements. Annual data represents a random draw within a specified cumulative distribution function. This means that, based on the magnitude of errors used in computing the aggregated statistics, interpretation of results based on such macroeconomic

variables is subject to inferential bias and depends on the margin of error of the computed macroeconomic variable. Some studies that have used annual data have investigated the relationship between inflation and gold price movements (Levin and Wright, 2006; Beckmann and Czudaj, 2013; Batten *et al.*, 2014); exchange rate-gold price nexus (Wang and Lee, 2011); interest rates – gold price dynamics (Faff and Hiller, 2004); output-gold price nexus (Lucey *et al.*, 2006); among others.

Secondly, the volatility or stochastic nature of gold price and its determinants is a very important factor to be considered in the investigation as this defines the impact that demand and supply forces of gold covariates have on its price. This brings in a methodological challenge where the influence of structural breaks needs to be considered in the investigation of these factors that determine the price of gold (Bai and Perron, 1998).

Thirdly, because market forces are critical in the investigation into what drives or hinders gold price movements, using factors that drive business or manufacturing activities such as stocks and bonds is of vital importance in the analysis of gold price movements. The use of such factors is directly linked to economic development movements (e.g., manufacturing) which influence fundamental macroeconomic factors such as interest rates, exchange rates, economic growth, labour movements (employment and unemployment), inflation, among others (Choudhry *et al.*, 2015).

Fourthly, the investigation into what determines movements in the price of gold is also critical for producers of gold. As of the year 2019, the top ten countries that produce gold in the world are China, Australia, Russia, United States of America, Canada, Indonesia, Peru, South Africa,

Mexico and Ghana. South Africa used to be the top producers in the world in 1970, producing approximately 1000 tons. However, annual output has declined ever since due to rising electricity and labour costs (US Global Investors, 2019). In addition, for countries such as South Africa whose main export is gold, price movements in gold prices influenced by its determinants, therefore, become critical as they directly impact movements in their currency prices (appreciation or depreciation).

The rest of the paper is structured as follows. Section 2 reviews both the theoretical and empirical literature and discusses the main stocks and bonds that are traded in the world. Section 3 discusses the multivariate and functional form of the determinants of gold prices linked to the two estimation techniques suggested above. Section 4 presents the empirical results mainly based on the ARDL-based error correction model that estimates both short- and long-run parameter estimations. Lastly, Section 5 concludes the paper and provides some policy implications derived from the estimated results that are relevant for both gold producers and investors.

2. Review of Theoretical and Empirical Literature

Gold is one of the securities that is traded on the stock market. The stock market is a platform where securities listed on either a public stock exchange or private stocks sold to investors through equity crowdfunding platforms are traded. Investments made in stocks are usually traded through brokers, either on-the-counter or online trading platforms. The business or financial interactions in the stock market involve the transfer of securities from a seller to a buyer or vice versa based on an agreed price. The economic agents that trade on the stock market usually range from an individual to large investors who are based anywhere in the world. Stocks are usually characterised

by the country in which they are registered and those that are relevant to this study are discussed below under data sources.

2.1 The Stock Market and the Efficient Market Hypothesis

The stock market has for centuries been considered as the main primary indicator of a country's economic development and strength (Bialkowski, 2015). As a security prices rise or fall, this will be reflected either by an increase or decrease in business activity, employment, consumption, among others, which in turn becomes either inflationary or deflationary thereby affecting key macroeconomic fundamentals such as interest rates, exchange rates, and overall output growth. Such phenomena necessitate Central Banks around the world to keep a watch on the dynamics of their stock markets in order to ensure smooth operations of the financial system as a whole so that it does not overheat (Nier, 2009).

Because stocks are assets whose price is determined by the interaction of buyers and sellers, one of the primary theoretical models that explain such interactions is the Efficient Market Hypothesis (EMH) and Random Walk Hypothesis (RWH) which emerged in the 1960s (Cootner, 1964; Fama 1970; Samuelson, 1973)². According to the EMH, in a competitive market, an asset price is expected to reflect all available information that will necessitate movements in that asset price until that information is no longer useful. The EMH is linked to the random walk theory through the fundamental theorem of asset pricing which states that, in the absence of arbitrage, the price of any stock will be represented by a random walk with a drift.

² We will not attempt to discuss variants to the EMH and RWH in this study as this is beyond the scope of this paper.

The random walk with a drift takes the following form:

$$Y_t = \alpha + Y_{t-1} + u_t \dots \dots \dots (1)$$

In equation (1), α is known as the ***drift parameter***. The name drift comes from the fact that if we write equation (1) as:

$$\Delta Y_t = Y_t - Y_{t-1} = \alpha + u_t \dots \dots \dots (2)$$

Then Y_t drifts upward or downward, depending on the drift parameter, α , being positive or negative. The movements therefore in this drift parameter will be influenced by any news available to economic agents. Fama (1970) categorized the available information into three categories: weak-form of information based on trends in the asset historical price; semi-strong information that is beyond historical prices and publicly available (e.g., central bank press conferences, interest rates movements, etc.); and strong information that goes beyond historical prices and public information and includes private information. It is against this backdrop that we propose a threshold in the computed adjusted R-squared of each period to represent periods of weak, semi-strong and strong information periods available to economic agents to influence the price of an asset. The adjusted R-squared usually lies within the (0, 1) threshold and represents a portion of the variance of the dependent variable that is explained by the set of covariates included in the regression model. We recommend any value of the adjusted R-squared that lies within the ranges of (0, 0.5] to represent weak-form of information, (0.5, 0.7] to represent semi-strong form of information, and (0.7, 1] to represent the strong-form of information available to economic agents to predict movements in the dependent variable.

2.2 The Bond Market and the Modern Monetary Hypothesis (Neo-Chartalism)

Much as the stock market is one of the most important ways in which companies raise money through initial public offerings and stock trading, the debt or bond market is also a financial marketplace where participants issue either new debt on the primary market or can buy and sell debt securities on the secondary market. The international bond market provides long-term financing to companies or governments around the world. Because the bond market is usually regulated, trading in this market is usually lower than on the stock market and the participants are mainly large investors and governments than individuals.

Much as some private companies do issue out corporate bonds, the largest supplier is a country's government through its central bank. Central banks around the world use the bond market to control interest rates and inflation during periods of economic growth or distress. The buying and selling of debt securities is usually used to either mop up or increase fiat currency or money stock. This is largely aimed at controlling inflation in an economy. Inflationary pressures which are usually created through fiscal policy interactions that target full employment necessitates investors to hedge their investments by opting for safe-haven securities such as gold and silver (Bialkowski, 2015). Since, through fiscal policy, any government has the power to levy taxes, determine how tax obligations are to be fulfilled as well as issue currency as the legal tender to pay for the taxes, governments, therefore, have the capability of determining the purchasing power of a currency (Tcherneva, 2002).

According to proponents of the modern monetary hypothesis, governments use taxation as a policy tool that regulates inflation and unemployment. During the 2008 financial crisis and the 2013 European sovereign debt crisis, the default risk of many economies in the developed world

increased substantially. To cushion such deflationary pressures, the countries' Central Banks carried out expansive monetary policies to support their governments' refinancing challenges and at the same time increasing inflation expectations. During this crisis period, gold investment became even more attractive, preserving its value amidst the crisis (Adrangi *et al.*, 2003; Worthington & Pahlavani, 2007; Blose, 2010).

3. Methodology and Estimation Techniques

Based on the Efficiency Market Hypothesis framework, a random walk model for gold price movements can be set as a function of both stocks and bonds as follows:

$$Au_t = f(Au_{t-1}, stocks_{i,t-j}, bonds_{i,t-j}, \varepsilon_t) \dots \dots \dots (3)$$

In equation (3), Au represents gold as a function of its lagged values, the drift parameters and an error term. The drift parameter has been split to account for influences from both stocks and bonds. Thus, changes in gold price movements can be represented as:

$$\Delta Au_t = f(stocks_{i,t-j}, bonds_{i,t-j}, \varepsilon_t) \dots \dots \dots (4)$$

According to equation (4), the price of gold Au_t will drift upward or downward, depending on whether the price movements of stocks and bonds are positive or negative subject to noise in the time series. Therefore, news affecting the stocks and bonds price movements available to economic agents are expected to influence price movements in gold subject to a random error.

3.1 A Linear Model Representation with Multiple Structural Breaks

In order to account for multiple structural breaks, the study employs two econometric methods. Firstly, the study employs Least Squares estimation that accounts for multiple structural breaks

proposed independently by Chong (1994), Liu *et al.* (1994) and Bai and Perron (1995). This approach has several advantages.

First, Bai and Perron (1995) argue that the identification of multiple structural breaks helps in understanding the events that lead to the identified structural change. Second, the identification of multiple structural breaks helps in forecasting as the most recent regime is likely to lead to better forecasting results than the sample as a whole (Bai and Perron, 1995). Third, Bai (1997) argues that taking into account multiple structural breaks in a time series helps improve robustness to misspecification particularly instability of time series, serial correlation, heteroskedasticity, as well as computational savings. Fourth, because the estimated linear regression will include different or multivariate parameters, the limiting distribution based on the structural breaks are generally asymmetric compared to simultaneous estimation based on the whole sample (Bai, 1997; Bai and Perron, 1998). Lastly, the number of least squares with breakpoint estimation is proportional to the sample size, thereby yielding different estimators from the multiple breakpoints identified (Bai, 1997).

When considering multiple structural breaks in a time series, Bai and Perron (1995) consider a multiple linear regression model with the following m partitions:

$$\begin{bmatrix} Au_1 = x'_1\beta + z'_1\delta_1 + \varepsilon_1 \\ \vdots \\ Au_T = x'_T\beta + z'_T\delta_{m+1} + \varepsilon_T \end{bmatrix} \dots \dots \dots (5)$$

Equation (5) can be presented as a vector representation of the linear regression system as follows:

$$\mathbf{Au} = \mathbf{X}\boldsymbol{\beta} + \mathbf{\bar{Z}}\boldsymbol{\delta} + \mathbf{E} \dots \dots \dots (6)$$

In equation (6), $\bar{\mathbf{Z}}$ is a block-diagonal matrix partitioning the multiple linear regressions at times (T_1, \dots, T_m) while \mathbf{X} represents a set of covariates available to predict movements in the dependent variable \mathbf{Au} . The goal of Bai and Perron (1995) approach is to estimate the unknown coefficients $(\boldsymbol{\beta}, \boldsymbol{\delta})$ on the assumption that the parameter estimates are different at time (T_1, \dots, T_m) .

3.2 Multivariate ARDL-Based Error Correction Representation

Once the multiple breakpoints have been identified in the sample used, the investigation into the determinants of gold prices is conducted using the Autoregressive Distributed Lag (ARDL) model suggested by Pesaran et al. (2001). The ARDL-based error-correction model follows a two-stage estimation approach and also has its advantages from other models. First, since multiple structural breaks means estimating individual regressions based on a sub-sample of the whole, the ARDL approach is helpful as it estimates robust parameters if the sample size is finite or small (Narayan, 2005). Second, unlike the least-squares estimation with breakpoints technique, the ARDL-based error correction model investigates both short- and long-run level relationships between the dependent variable and the selected covariates (Chirwa and Odhiambo, 2019). Third, unlike the least squares with breakpoints option, the ARDL model corrects for endogeneity between the dependent variable and its regressors through the inclusion or exclusion of lags (Pesaran and Shin, 1999). Finally, the ARDL bounds testing procedure is superior to many estimation techniques including the least squares estimation with breakpoints as it can be applied regardless of whether the dependent variable and its regressors are integrated of either order one or zero (Pesaran *et al.*, 2001).

In order to incorporate multiple structural breaks identified through the Bai and Perron (1995) test procedure, the ARDL representation of the empirical model can be expressed as a vector representation as follows:

$$\begin{bmatrix} \Delta \ln Au_1 = \beta_0 + \beta_1 T_1 + \sum_{i=1}^n \beta_{2i} \Delta \ln Au_{1-i} + \sum_{i=0}^n \beta_{3i} \Delta \ln x_{j,1-i} + \sum_{i=0}^n \beta_{4i} \Delta \ln y_{j,1-i} + \alpha_1 \ln Au_{-1} + \alpha_2 \ln x_{-1} + \alpha_3 \ln y_{-1} + \varepsilon_1 \\ \vdots \\ \Delta \ln Au_T = \beta_0 + \beta_1 T_m + \sum_{i=1}^n \beta_{2i} \Delta \ln Au_{T-i} + \sum_{i=0}^n \beta_{3i} \Delta \ln x_{j,T-i} + \sum_{i=0}^n \beta_{4i} \Delta \ln y_{j,T-i} + \alpha_1 \ln Au_{T-1} + \alpha_2 \ln x_{T-1} + \alpha_3 \ln y_{T-1} + \varepsilon_T \end{bmatrix} \dots (7)$$

In a vector representation, equation (7) can be represented as follows:

$$\Delta \ln \mathbf{Au}_t = \beta_0 + \sum_{i=1}^n \phi_i \Delta \ln \mathbf{Au}_{t-i} + \sum_{i=0}^n \boldsymbol{\rho}'_{ji} \Delta \ln \mathbf{y}_{j,t-i} + \delta'_i \ln \mathbf{z}_{t-1} + \boldsymbol{\varepsilon}_t \dots \dots \dots (8)$$

In equation (8), \mathbf{Au}_t represents a $(k \times 1)$ column vector of the dependent variable (gold price movements) and its explanatory variables represented by stocks and bonds, and any other relevant information that is useful to predict movements on gold prices are grouped in the \mathbf{y} vector. In the same equation, ϕ_i represent a scalar matrix with the coefficients of the lagged dependent variable; $\boldsymbol{\rho}'_{ji}$ represent a $(k \times 1)$ row vector representing short-run multipliers (elasticities) of coefficients of the explanatory variables. The coefficient matrix δ'_i is a $(k \times 1)$ row vector of coefficients of \mathbf{z}_{t-1} representing long-run multipliers (elasticities) of both the dependent and explanatory variables lagged one period. The deterministic regressor is represented by β_0 and is included based on the limiting distribution or data generating process of the underlying data used. For each multivariate equation, the joint null hypothesis is that for all the identified multiple structural breaks, the regressand and its lagged variables are cointegrated. Equation (8) is estimated using Ordinary Least Squares (OLS) to test the existence of a long-run equilibrium relationship between the regressand and its regressors.

Once the long-run relationships are confirmed an ARDL-based error correction model (ECM) can be specified in matrix form as follows:

$$\Delta \log \mathbf{A} \mathbf{u}_t = \sum_{i=0}^n \boldsymbol{\rho}'_{ji} \Delta \log \mathbf{y}_{j,t-i} + \delta \mathbf{ECM}_{t-1} + \varepsilon_t \dots \dots \dots (9)$$

The ARDL-based error correction term (ECM) in equation (9) measures the speed of adjustment towards the long-run equilibrium path (Chirwa and Odhiambo, 2019). The coefficient of the ECM is expected to be negative and statistically significant. The ECM represents the roots of the ARDL based error correction model and is expected to lie outside the unit circle to guarantee that the coefficient of the error correction term is less than zero or within the (0, -1) space (Pesaran et al., 2001). This is important as it ensures the stability of the ARDL representation in the long run as well as a stationary process where all variables are either $I(0)$ or $I(1)$ variables.

For the bounds test procedure to be valid, all variables are expected to be either integrated of order zero, $I(0)$ or integrated of order one, $I(1)$. It is, therefore, important to test for unit root in the time series of interest. Otherwise, if any of the variables are integrated of order two, $I(2)$, the bounds test cannot be applied (see also Odhiambo, 2013). For this purpose, the study uses the conventional unit root tests such as the Augmented Dickey-Fuller (1979) unit root test that takes into account the presence of serial correlation in the time series data; the Perron (1990) innovation outlier model that accounts for the presence of a structural break in the time series data; and the Elliott, Rothenberg and Stock (1996) Dickey-Fuller Generalized Least Squares (DF-GLS) unit root test that detrends the time series data. In addition, the study employs four multiple-series or group unit root tests, namely: (i) one test that assumes a common unit root process (Levin *et al.*, 2002); (ii) three individual unit root tests suggested by Im *et al.* (2003); and (iii) the Fisher-type tests based on the Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) *chi* – square statistics (see Maddala and Wu 1999; Choi 2001).

3.3 Data Sources and Definition of Variables

The study uses daily data covering the period December 19, 2018 to May 15, 2020 sourced from www.investing.com. The determinants of gold price movements, as suggested above, are based on stocks and bonds. There are several stock markets in the world, but the major ones that are frequently referenced include NASDAQ index (IXIC), Dow Jones Industrial (DJI) index, S&P 500 (US500) index, and New York Stock Exchange (NYSE) composite index based in the USA; London Stock Exchange (LSE) group PLC index based on London, England; Nikkei 225 (JP225) index based in Tokyo, Japan; and the *Deutscher Aktienindex* (DAX) or German Stock Index based in Germany. To also incorporate cryptocurrencies which similarly works as a safe haven based on a virtual currency, the study uses bitcoin as one of the stocks that is traded on the stock exchange since December 19, 2018.

Similarly, much as there are many bond fund markets in the world, there are five top international bond funds that are usually traded, and they are all based in the United States of America (USA). These include: the PIMCO International Bond Fund (PFORX); the PIMCO Emerging Markets Local Currency and Bond Fund (PELBX); Goldman Sachs Emerging Markets Debt Fund (GSDIX); T. Rowe Institutional Emerging Markets Bond Fund (PRSNX); and the GMO Emerging Country Debt Fund (GMCDX). These international bond funds usually trade investment-grade sovereign debt from emerging markets. The PFORX is a mutual fund that trades mostly in investment-grade securities and it has holdings in a number of countries in Europe, Australia, China, Canada, among others. The PELBX bond fund usually trades in local-currency denominated debt and their primary investment is in government bonds. The GSDIX bond fund also trades mostly in investment-grade government bonds mainly in Latin America, Middle East,

Africa, Central and Eastern Europe, and Asia. The PRSNX bond fund trades in government and corporate bonds but unlike the other funds, it includes lowest-rated bonds where some have defaulted. Lastly, the GMCDX bond fund trades in government bonds with the majority being investment-grade sovereign debts³.

Another useful determinant that we included, apart from stocks and bonds, is called the Chicago Board Options Exchange (CBOE) volatility index. This is a statistical measure of the degree of variation that measures the level of risk or stress in the market based on stock price movements over a 30-day forward-looking period. The higher the volatility in the stock market, the higher is the implied CBOE volatility index implying high risk⁴.

Therefore, the estimated model is represented as follows:

$$\begin{aligned} & LnAu_t \\ & = f \left(\begin{array}{l} lnAu_{t-1}, lnbtct_{-i}, lnixic_{t-i}, lndji_{t-i}, lnus500_{t-i}, lnnyse_{t-i}, lnlse_{t-i}, lnjp225_{t-i}, \\ lnide30_{t-i}, lngsdix_{t-i}, lnpforx_{t-i}, lngmcdx_{t-i}, lnpebxb_{t-i}, lnprsnx_{t-i}, lncboe_{t-i}, \varepsilon_t \end{array} \right) \dots \dots (10) \end{aligned}$$

4. Empirical Analysis

4.1 Group-Based Unit Root Tests

The results of the group unit root tests based on the variables used in equation 10 are presented in Table 1.

³ For more information, visit <https://www.investopedia.com/articles/investing/010416/top-5-international-bond-funds-2016.asp>

⁴ This information is sourced from www.cboe.com

Table 1: Group Unit Root Test Results

Group Unit Root Test Method	Statistic	Unit Root Status	Statistic	Unit Root Status
	Stationarity of all Variables in Levels		Stationarity of all Variables in 1 st Difference	
Null Hypothesis: Unit root (assumes common unit root process)				
Levin <i>et al.</i> (2002)	-0.8543 [0.1965]	Unit root	-31.471* [0.0000]	Stationary
Null Hypothesis: Unit root (assumes individual unit root process)				
Im <i>et al.</i> (2003)	-2.0882* [0.0184]	Stationary	-37.973* [0.0000]	Stationary
ADF	41.663** [0.0466]	Stationary	1004.26* [0.0000]	Stationary
PP	29.206 [0.4021]	Unit root	1940.95* [0.0000]	Stationary

Note: for all p-values: * 1% significance level; ** 5% significance level; *** 10% significance level.

The results in Table 1 reveal that the null hypothesis of unit root in levels is not rejected based on the Im *et al.* (2003) and ADF *chi* – square statistics depicting that the variables used in our study are stationary in levels while the Levin *et al.* (2002) common unit root tests and the PP *chi* – square statistics show that the variables used have a unit root. However, after taking first differences, the results show that the null hypothesis of unit root is strongly rejected at the 1% significance level meaning that all computed statistics are stationary. This entails that all variables used in our study are either integrated of order one or zero. Therefore, the ARDL bounds testing procedure can be used in our study.

4.2 Multiple Structural Breakpoint Test

In order to determine the regime breakpoints of our sample, the study employs the Bai (1997) sequential method (L+1 breaks vs. L) to determine the number of breaks that the study should estimate using the ARDL bounds testing procedure. Based on this test, four regimes are identified

for the study period December 19, 2018 to May 15, 2020 and the results are presented in Table 2 below.

Table 2: Regime Breakpoint Test Results

Break Period	Start Period	End Period	Computed $F - \text{Statistic}$	Observations
Break 0 vs. 1	12/19/2018	05/17/2019	39.035**	103
Break 1 vs. 2	05/20/2019	08/06/2019	9.2326**	55
Break 2 vs. 3	08/07/2019	03/02/2020	2.7577**	143
Break 3 vs. 4	03/03/2020	05/15/2020	0.0000	53
Null Hypothesis: No Structural Breaks				

*Note: for all p-values: * 1% significance level; ** 5% significance level; *** 10% significance level.*

As illustrated in Table 2, the results show that there are three breakpoints that are statistically significant at the 5% significance level. These three structural breaks are linked to several global macroeconomic events that happened. The May 2019 structural break was due to US trade tensions with China that initiated stock sell-offs mainly of technology-driven companies sparked by the US President's tweets on May 5, 2019 to hike tariffs on US\$200 billion worth of Chinese goods. The US government lived to its promise and raised such tariffs on May 10, 2019 and banned US companies from doing business with Huawei, a Chinese company⁵. At the same time China retaliated by raising levies on US\$60 billion of US goods. The trade fears continued in August 2019 (second structural break) that resulted from the continued escalation of US-China trade tensions and an early indication of recession signalled by the bond market⁶. The last structural break that happened in March 2020 was due to the Corona Virus (COVID-19) pandemic that hit the global market strongly with the biggest sell-offs in the history of the stock market⁷. The

⁵ See <https://www.cnbc.com/2019/05/31/the-markets-drop-in-may-felt-serious-but-it-is-normal-for-stocks.html>

⁶ See <https://www.cnbc.com/2019/08/31/august-was-a-wild-month-for-wall-street-heres-what-happened.html>

⁷ See <https://www.cnbc.com/2020/06/10/stock-market-futures-open-to-close-news.html>

reference periods are also sequentially determined, meaning that when estimating the ARDL-based error correction model, four regime breakpoints should be taken into account.

4.3 ARDL Bounds Test for Cointegration

The study employs the Pesaran *et al.* (2001) bounds test for long-run relationships. The Schwarz-Bayesian Criteria (SBC) is employed to determine the appropriate optimum lag-length for the four ARDL equations estimated based on the four identified breakpoint regimes in Table 2. The optimal lag-length selection criterion is calculated based on the lowest SBC. This methodology is useful as it tends to under-fit the model of interest given that the optimal lag length chosen for the estimated gold price movement model is up to 2 lags. The cointegration results are presented in Table 3.

Table 3: ARDL Bounds Test Results based on Regime Breakpoint

Regime Breakpoint	ARDL Function				Case	Value (F-statistic)	Cointegration Status
Breakpoint 1	ARDL (1,1,2,1,0,0,0,0,0,1,1,1,1,1)				II	2.83***	Cointegrated
Breakpoint 2	ARDL (2,1,1,1,1,0,0,0,1,0,0,0,1,1)				II	2.90***	Cointegrated
Breakpoint 3	ARDL (1,0,0,0,0,0,2,2,1,1,2,2,2,2,0)				III	6.58*	Cointegrated
Breakpoint 4	ARDL (2,2,2,2,2,2,2,2,2,1,0,2,2,1,2)				II	5.09*	Cointegrated
Null Hypothesis: No long-run relationships exist (Case II, III)							
	1%		5%		10%		
Case	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$	
II	2.41	3.61	1.98	3.04	1.76	2.77	
III	2.54	3.86	2.06	3.24	1.83	2.94	

Source: Computed critical values from Pesaran *et al.* (2001). Note: for all *p*-values: * 1% significance level; ** 5% significance level; *** 10% significance level.

The results illustrated in Table 3 reveal that all estimated regime breakpoints are cointegrated at either the 1% or 10% level of significance, thereby confirming the existence of a long-run level relationship between the dependent variable, gold price movements, and its set of covariates presented in equation 10.

4.4 Empirical Analysis of Regime Breakpoint ARDL-based Error Correction Model

Table 4 presents the estimated multiple breakpoint ARDL-based error correction results. There are two panels presented in Table 4. The first panel presents long-run results while the second panel presents short-run growth estimates of the included lags of the dependent and regressors. There are four important findings to the results presented in Table 4.

Firstly, the parameter estimates for each breakpoint regime are different signifying the importance of accounting for multiple breakpoints in a time series. Secondly, both the short- and long-run results reveal that, depending on the breakpoint regime, the estimated coefficients are either positive or negatively associated with gold price movements, except for long-run price movements of German stock prices (DE30) that are consistently negative regardless of breakpoint regime. Thirdly, as discussed on the role that the adjusted R-squared can play in determining weak, semi-strong, and strong information as proposed by Fama (1970), the results in Table 4 show that the third breakpoint regime that runs from August 7, 2019 to January 2, 2020⁸ was characterised by weak information with an estimated adjusted R-squared of 0.07. The first breakpoint regime running from December 19, 2018 to May 17, 2019 reveals semi-strong information available to investors with an estimated adjusted R-squared of 0.68. Periods where investors had strong information include the second (May 20 to August 6, 2019) and fourth (March 3 to May 15, 2020) breakpoint regimes that revealed an estimated adjusted R-squared of 0.81 and 0.94, respectively.

⁸ The third breakpoint was reduced in size by two months in order to correct for serial correlation and unstable standard errors (cumulative sum of squares).

Table 4: Estimated Breakpoint Regime Results (Short- and Long-run Coefficients)

Regressor	Coefficient Breakpoint 1	Coefficient Breakpoint 2	Coefficient Breakpoint 3	Coefficient Breakpoint 4
Panel 1 – Estimated Long-Run Coefficients (Elasticities) [Dependent Variable: Log of Gold Price, $\log(xausd)_t$]				
$\log(btcusd)_t$	0.0237	0.0226	-0.8240	0.1886**
$\log(ixic)_t$	1.7161	-1.2929	0.0518	-0.7857
$\log(dji)_t$	0.6531	1.3847***	-0.1620	-1.6887
$\log(us500)_t$	-2.5813	-0.2823	0.1606***	2.2526
$\log(nyse)_t$	0.2145	-1.1286	1.2640	0.7551
$\log(lse)_t$	-0.1969	0.1526***	-6.2866***	0.0265
$\log(jp225)_t$	-0.0617	0.0912	7.8131***	1.0248*
$\log(de30)_t$	-0.3885	-0.0318	-3.5941	-0.6266*
$\log(gsdix)_t$	-1.1051	6.8387***	-0.0589	2.2170***
$\log(pforx)_t$	3.8992**	-5.6826***	2.8310***	1.4224
$\log(gmcdx)_t$	1.0076	-1.5935	-0.6094	-2.2279**
$\log(cboe)_t$	-0.0093	-0.1032	-0.4654	0.2156**
$\log(pelbx)_t$	1.0180**	-0.5200	-1.3940	-1.9537*
$\log(psrnx)_t$	-3.1279	3.3530	6.1283**	2.0463**
C_t	2.2388	4.5162		-1.4569
Panel 2 – Estimated Short-Run Coefficients (Elasticities) [Dependent Variable: change in log of Gold price, $\Delta \log(xausd)_t$]				
C_t			0.0009	
$\Delta \log(xausd)_{t-1}$		-0.3081*		0.5612*
$\Delta \log(btcusd)_t$	0.0670*	0.0338*		0.1017*
$\Delta \log(btcusd)_{t-1}$				-0.1169*
$\Delta \log(ixic)_t$	0.1008	-1.3063*		-1.1854*
$\Delta \log(ixic)_{t-1}$	0.0724*			0.8822*
$\Delta \log(dji)_t$	0.3784*	-0.4321		-1.6370*
$\Delta \log(dji)_{t-1}$				1.5767*
$\Delta \log(us500)_t$		2.6188*		3.2844*
$\Delta \log(us500)_{t-1}$				-3.5349*
$\Delta \log(nyse)_t$				-0.0859
$\Delta \log(nyse)_{t-1}$				0.8095*
$\Delta \log(lse)_t$			0.0146	0.2446*
$\Delta \log(lse)_{t-1}$			-0.0304	0.1462*
$\Delta \log(jp225)_t$			0.2089**	0.2837*
$\Delta \log(jp225)_{t-1}$			0.0892	-0.2054*
$\Delta \log(de30)_t$			-0.1823***	0.0650***
$\Delta \log(de30)_{t-1}$				0.2226*
$\Delta \log(gsdix)_t$		1.3800*	0.7640**	0.2193
$\Delta \log(pforx)_t$	0.2492		0.0284	
$\Delta \log(pforx)_{t-1}$			-0.0095	
$\Delta \log(gmcdx)_t$	-0.5698*		-0.1192	-0.8207*
$\Delta \log(gmcdx)_{t-1}$			0.0179	-0.8822*
$\Delta \log(cboe)_t$	0.0083		0.0086	0.1528*
$\Delta \log(cboe)_{t-1}$			0.0080	-0.1245*
$\Delta \log(pelbx)_t$	0.5498*	0.3074	-0.0944	-1.1496*
$\Delta \log(pelbx)_{t-1}$			-0.4300***	
$\Delta \log(psrnx)_t$	2.6255*	2.9791*		1.2748*
$\Delta \log(psrnx)_{t-1}$				1.2447*
ECM_{t-1}	-0.2042*	-0.4413*	0.0010	-0.9353*
R^2	0.6764	0.8379	0.2077	0.9707
Adjusted R^2	0.6444	0.8098	0.0710	0.9436

Source: Authors' Calculations. Note: * 1% significance level; ** 5% significance level; *** 10% significance level.

Lastly, the speed of adjustment varies within breakpoint regimes depending on the strength of information available to investors. The computed error correction term ranges from (0, -0.94] with the lowest value in the third period and the largest value computed in the last breakpoint period.

In the first breakpoint regime, the results reveal that only movements in the bond market exposed a significant positive long-run level relationship between price movements in Pimco international bond funds and T. Rowe price global multi-sector bond funds. In the second breakpoint regime, the results reveal a positive relationship between stock price movements in the Dow Jones Index, the London Stock Exchange market, and bond price movements in the Goldman Sachs emerging markets debt fund. A negative long-run relationship is revealed between bond price movements in the Pimco international bond funds and gold prices in the same period. In the third breakpoint regime, a significant positive relationship was revealed between gold price movements and Nikkei stock prices, and bond price movements of Goldman Sachs emerging markets debt fund and the T. Rowe price global multi-sector bond fund. Conversely, a negative long-run relationship was present between gold price movements and German stock price movements and bond price movements of Pimco emerging markets local currency bond funds.

In the last breakpoint regime, which Bai and Perron (1995) regard as the most relevant period, the study reveals a number of significant associations in both the stock and bond markets. In the stock market, the study reveals a significant positive association between gold price and bitcoin, LSE, and Nikkei stocks, while German stocks reveal a negative long-run relationship with gold price movements. In the bond market, the long-run results reveal a significant positive relationship between gold price movements, Goldman Sachs emerging markets debt fund, CBOE volatility index, and T. Rowe price global multi-sector bond funds and a significant negative association

between gold price movements, and bond price movements in Gmo emerging country debt fund, and Pimco emerging markets local currency bond funds.

The short-run results, on the other hand, paint a different picture. In the first breakpoint regime, the study reveals that a positive relationship exists between gold price and stock price movements in bitcoin, Dow Jones Index, and the lag of NASDAQ stocks. In the bond market, the growth of gold price movements is positively associated with price growth in Pimco emerging markets local currency and T. Rowe price global multi-sector bond funds, but negatively associated with the growth of prices of Gmo emerging country debt fund. In the second breakpoint regime, the results show positive association between the growth of gold price movements, bitcoin and S&P500 stocks and a negative association with the growth of one-period lag of gold prices and NASDAQ stocks. In the bond market, the short-run results reveal only a positive association between the growth of gold prices, Goldman Sachs emerging markets debt fund, and T. Rowe price global multi-sector bond funds. In the third breakpoint regime, the results reveal a positive association between the growth of gold prices and Nikkei stocks and a negative association with German stocks, both in the current period. In the bond market, the growth of gold prices is positively associated with the growth of Goldman Sachs emerging markets debt fund and negatively associated with one period lag of the growth of Pimco emerging markets local currency bond funds.

In the last period, again the most important as per Bai and Perron (1995), the results show a number of significant findings. In the stock market, the results show that the growth of gold prices in the short run is positively associated with the overall growths of NYSE, LSE, Nikkei, German stocks, and a one-period lag of gold prices; and negatively associated with the overall growths of bitcoin,

NASDAQ, Dow Jones Index, and S&P500 stocks. In the bond market, the short-run results show that the growth of gold prices is positively associated with the growths of CBOE volatility index and T. Rowe global multi-sector bond funds; and negatively associated with the overall growths of Gmo emerging country debt fund, and Pimco emerging markets local currency bond funds.

4.5 Post-Estimation Diagnostic Tests

In order to ensure that the parameter estimates of our ARDL model are valid, several post-diagnostic tests are reported in Table 5. These include stability tests based on the CUSUM and CUSUMSQ tests; and residual tests based on the Breusch-Godfrey serial correlation test, the Breusch-Pagan-Godfrey test for heteroskedasticity, and Normality tests.

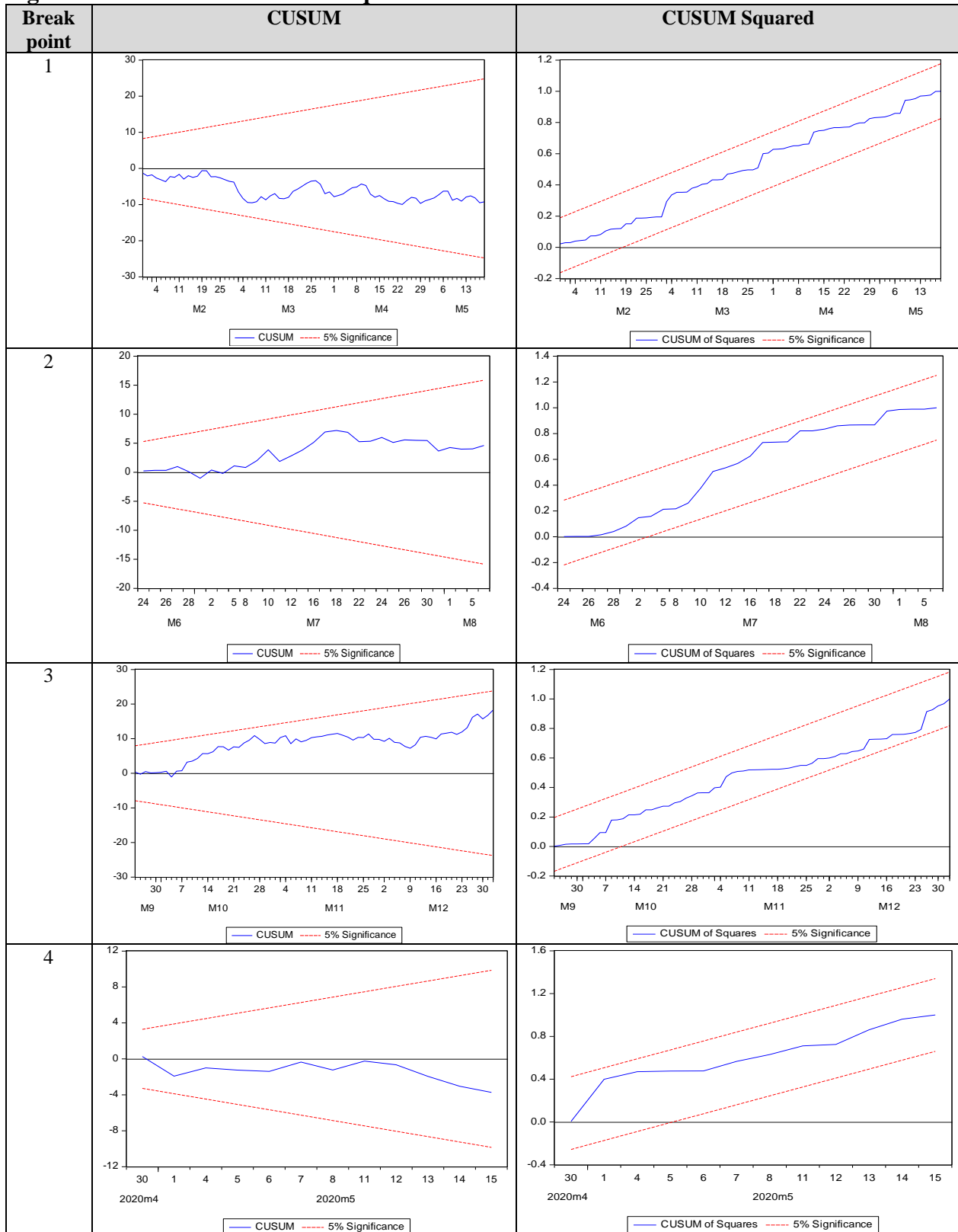
Table 5: Post-Estimation Diagnostic Tests

Test Statistic	Period 1	Period 2	Period 3	Period 4
Breusch-Godfrey Test: No Serial Correlation F (1,28)	0.0610 [0.9409]	1.6394 [0.2116]	0.6694 [0.5153]	2.6881 [0.1163]
Breusch-Pagan-Godfrey Test: No Heteroskedasticity F (1,40)	0.9316 [0.5611]	1.3175 [0.2342]	1.0277 [0.4485]	0.4058 [0.9837]
Normality: CHSQ (2)	0.0553 [0.9727]	0.7452 [0.5153]	0.4985 [0.7793]	3.9559 [0.1384]

*Note: for all p-values: * 1% significance level; ** 5% significance level; *** 10% significance level.*

The inclusion of normality tests is used to confirm Bai and Perron's (1995) assertion on the asymmetric distribution of partitioned time series when using the breakpoint regime tests. The CUSUM and CUSUM squared results are presented in Figure 1. The results shown confirm the stability of the estimated breakpoint ARDL-based error correction models used in this study.

Figure 1: CUSUM and CUSUM Squared Tests



Source: Author Calculations in Eviews 9.5.

The results in Table 5 and Figure 1 confirm that the four estimated ARDL-based error correction models with multiple breakpoints do not suffer from any misspecification as the study results cannot reject the null hypothesis of serial correlation, heteroskedasticity or normality tests – despite Bai and Perron’s (1995) assertion of asymmetric distribution once structural breakpoints are taken into account of a full sample that is normally distributed.

5. Conclusion and Policy Implications

The study investigates the determinants of gold price movements on the stock market using daily data from December 19, 2018 to May 15, 2020, conditioned by movements in other stocks and bonds on the global market. The modelling approach used was based on the Efficiency Market Hypothesis and Modern Monetary Hypothesis. The investigation also considered the identification of structural breakpoint regimes using Bai and Perron (1995) methodology in the analysis to ensure parameter consistency in the time series data used before employing the ARDL-based error correction framework. The three structural breaks identified were mainly driven by US-China trade tensions and the COVID-19 pandemic that led to a global recession and a huge sell-off in the global financial markets.

The EMH was of particular importance as it assisted in determining how information is used by economic agents or investors on the stock market to determine movements in gold prices. There were four regimes that were identified using Bai and Perron (1995) methodology. However, they do assert that it is the results of the last regime that are of paramount importance when describing the future trends in the dependent variable conditioned on the set of covariates used. In the last regime, that ran from March 3 to May 15, 2020, the results revealed a significant positive long-run association between gold price movements, London Stock Exchange (LSE), Nikkei (JP225)

stocks, T. Rowe global multi-sector bond funds, and CBOE volatility index both in the short- and long-run. Conversely, in the bond fund market, the results showed a significant negative relationship between Gmo emerging country debt fund, Pimco emerging markets local currency bond funds and gold price movements both in the short- and long-run.

While German stocks revealed a negative association in the long-run, the results in the short-run reveal a positive relationship with gold price movements. The same applied to bitcoin stock price movements that revealed a positive association in the long-run and a negative relationship in the short-run. During the same period, Goldman Sachs bond funds had a significant positive relationship with gold price movements only in the long-run. The only stocks that revealed a significant positive relationship only in the short run were NYSE stocks. In contrast, NASDAQ, DJI, and US500 all revealed a significant negative short-run relationship with gold price movements.

There are four key findings in this study that have significant policy implications. Firstly, stocks have a significant positive association with gold price movements and most stocks have gold mining companies listed. For instance, on the LSE some of the top gold mining companies listed include Goldplat Plc. (South Africa), Goldstone Resources (Guyana), Great Western Mining Plc. (Nevada), Greatland Gold (Western Australia), Greenore Gold Plc. (Scotland), among others; and the Nikkei is home to most Japanese and Chinese gold mining stocks. The finding that shows a positive correlation between stocks and gold price movements is significant for both investors and policy makers as an important signal to either invest in gold as a stock when stock prices go up or sell-off gold when stock prices fall. Conversely, the bond market results that show mostly a negative association with gold price movements is an important indicator of a recession which

creates uncertainty on the global market and hence a practical guide to both investors and policy makers to invest in gold.

Secondly, the study found that if structural breakpoints are considered in financial time series, parameter estimates are bound to be different for each breakpoint regime signifying the importance of accounting for multiple breakpoints in a time series. In the daily time series used in this paper, three structural breakpoints were identified that were led by US-China trade tensions and the advent of the COVID-19 pandemic in March 2020. These events sent shockwaves on the global financial market leading to massive sell-offs in the stock market. The March 2020 breakpoint particularly led to massive sell-offs in the stock market leading to huge drops in gold prices as well revealing a positive correlation as supported by the results presented in this study. This also has important policy implications for investors and policy makers to always consider ‘*stability news*’ that is likely to move stocks and bond fund prices significantly as vital information to include whenever investment policies or decisions are being designed.

Thirdly, the study also found that depending on the breakpoint regime, the estimated coefficients of the covariates are associated with different signs depending on the information available during the breakpoint period. Only long-run price movements of German stock prices (DE30) were consistently negative regardless of breakpoint regime. The rest of the covariates revealed different signs when different breakpoint regimes were considered. This is important, as it also reveals the dynamic nature of stock and bond fund prices in informing movements in gold prices in the future. This information also presents the important assumption suggested by Bai and Perron (1995) that it is only the latest information or news that is very critical to policy making and a clear indication that policies affecting gold prices should frequently be reviewed as new information is generated.

Historical information is not always dynamic, and what happened in the past is not likely to repeat itself in the future, particularly during dramatic events that are always unique.

Last but not least, is related to the EMH as postulated by Fama (1970) in determining weak, semi-strong, and strong information. The study used the computed adjusted R-squared for each breakpoint period to determine how weak or strong the available information was to investors. The results showed that the third breakpoint regime running from August 7, 2019 to January 2, 2020 had weak information with an estimated adjusted R-squared of 0.07, while the first breakpoint regime running from December 19, 2018 to May 17, 2019 had semi-strong information available to investors with an estimated adjusted R-squared of 0.68. The strong information was available to investors during the second (May 20 to August 6, 2019) and fourth (March 3 to May 15, 2020) breakpoint regimes, which revealed an estimated adjusted R-squared of 0.81 and 0.94, respectively. This information is also important to investors and policy makers as it could also signify ‘*tranquillity before chaos*’ as this was a period that led into one of the great recessions the global financial market has experienced since the 1920s – the COVID-19 pandemic.

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